Carving UI Tests to Generate API Tests and API Specification

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***Abstract*—Modern web applications make extensive use of API calls to update the UI state in response to user events or server-side changes. For such applications, API-level testing can play an important role, in-between unit-level testing and UI-level (or end-to-end) testing. Existing API testing tools require API specifications (e.g., OpenAPI), which often may not be available or, when available, be inconsistent with the API implementation, thus limiting the applicability of automated API testing to web applications. In this paper, we present an approach that leverages UI testing to enable API-level testing for web applications. Our technique navigates the web application under test and automatically generates an API-level test suite, along with an OpenAPI specification that describes the application's server-side APIs (for REST-based web applications). A key element of our solution is a dynamic approach for inferring API endpoints with path parameters via UI navigation and directed API probing. We evaluated the technique for its accuracy in inferring API specifications and the effectiveness of the "carved" API tests. Our results on seven open-source web applications show that the technique achieves 98% precision and 56% recall in inferring endpoints. The carved API tests, when added to test suites generated by two automated REST API testing tools, increase statement coverage by 52% and 29% and branch coverage by 99% and 75%, on average. The main benefits of our technique are: (1) it enables API-level testing of web applications in cases where existing API testing tools are inapplicable and (2) it creates API-level test suites that cover server-side code efficiently while exercising APIs as they would be invoked from an application's web UI, and that can augment existing API test suites.**

***Index Terms*—Web Application Testing, API Testing, Test Generation, UI Testing, End-to-end Testing, Test Carving, API Specification Inference**

I. Introduction

Software applications routinely use web APIs for establishing client-server communication. In particular, they increasingly rely on web APIs that follow the REST (REpresentational State Transfer) architectural style [1] and are referred to as RESTful or REST APIs. A typical REST API call starts with an HTTP request made by the client, e.g., the front-end of a web application running in the browser, and ends with a response sent by the server or the back-end of the application. To help clients understand the operations available in a service and the request and response structure, REST APIs are often described using a specification language, such as OpenAPI [2], API Blueprint [3], and RAML [4].

Web application testing is typically performed at multiple levels, each employing different techniques/tools and with different end goals. Unit-level testing of client- and server-side components focuses on validating the low-level algorithmic and implementation details and achieving high code coverage. In contrast, UI-level testing (also called end-to-end testing) focuses on covering navigation flows from the application's web UI, exercising various tiers of the application in end-to-end manner. In between unit and UI testing, API testing places the focus of testing on the operations of a service as well as sequences of operations; it exercises the server-side flows more comprehensively than unit testing but without going through the UI layer. API-level testing is guided by code-coverage goals as well as API-coverage goals (e.g., [5]).

For web applications that use RESTful APIs whose specifications are available, a number of automated testing techniques and tools (e.g., [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]) could be leveraged for API-level testing. These tools take as input an API specification, and automatically generate test cases for exercising API endpoints defined in the specification. However, in practical scenarios, using these tools may not always be possible.

First, for applications that do not have RESTful APIs, such tools are inapplicable. This rules out large classes of web applications, such as Java Enterprise Edition as well as legacy web applications, which could benefit just as well from automated API-level testing. Second, for web applications with RESTful APIs, API specifications may not be available. This can occur because of different reasons, often because the APIs are meant for use by the specific web application only or applications within an enterprise, and not exposed for invocation by external clients. Thus, formal API documentation is considered less important and not done due to development pressures or other factors. Moreover, even when API specifications are available, they can be obsolete and inconsistent with API implementations [19]. As a web application and its APIs evolve, the specifications—which can be large and complex—often fail to co-evolve due to the maintenance effort involved.[1]

[1]Although there exist tools for automatically documenting REST APIs (e.g., SpringFox [20] and SpringDoc [21]), which can reduce the cost of keeping API specifications up-to-date with API implementations, their applicability is limited (e.g., to web applications implemented using Spring Boot [22]).

In this work, we address the challenges of enabling automated API-level test generation universally for web applications, irrespective of whether they use RESTful web services, and automatically inferring OpenAPI specifications for web applications that use RESTful APIs. We present a dynamic technique that executes the web application via its UI to automatically create (1) API-level test cases that invoke the application's APIs directly, and (2) a specification describing the application's APIs that can be leveraged for development and testing purposes.

Although prior work has investigated carving unit-level tests from system-level executions using code-instrumentation techniques (e.g., [23], [24], [25]), no technique exists for carving API-level test cases from UI paths or test cases.

Our technique monitors the network traffic between the browser and the server, while navigating the application's UI, and records the observed HTTP requests and responses. Then, it applies filtering to exclude the requests (and their responses) that are considered unnecessary for API testing. Next, it builds an API graph from the filtered requests and analyzes the graph to infer a specification that captures API endpoints (or resource paths), the applicable HTTP methods (e.g., GET, POST), and the request/response structure for each API operation (combination of HTTP method and API endpoint). A key feature of our technique is that it infers path parameters or variables for API endpoints from concrete endpoint instances observed during the navigation of UI paths. Moreover, it uses a novel algorithm for directed API probing and API graph expansion to discover more concrete endpoint instances that would otherwise be missed by UI path navigation alone.

The generated API specification can serve as documentation for server-side APIs of a web application (even if the APIs are not RESTful) and also be fed as input into an existing API testing tool for automated test generation (e.g. [6], [7], [8], [10], [12]) or used for checking inconsistencies in existing API specifications (for RESTful APIs).

The "carved" API test cases are derived from UI paths. Because these tests bypass the UI layer, they execute much more efficiently and are less prone to brittleness than UI-level tests. Yet, they cover the same server-side code as the UI paths from which they are derived and exercise the APIs in ways that they would be invoked from the UI.

We implemented our technique in a tool called APICARV that takes as input a UI test suite (generated or manually written) and carves API test cases and an OpenAPI specification.

We conducted an empirical study on seven open-source web applications to evaluate the technique's effectiveness in carving API tests and inferring OpenAPI specifications. With respect to test carving, our results are two-fold. First, they quantify the expected benefits of carved API tests: the tests attain similar coverage as the UI test paths from which they are derived, but at a fraction of the execution cost of UI tests: on average, more than 10x reduction in test execution time. Second, our results illustrate that carved API tests can increase the coverage achieved by two automated API test generators, EvoMaster [26], [6] and Schemathesis [27], [28]: on average, 52% (99%) gains in statement (branch) coverage for EvoMaster and 29% (75%) statement (branch) coverage gains for Schemathesis. Finally, for OpenAPI specification inference, our results show that the technique computes API endpoints (or resource paths) with 98% precision and 56% recall against the ground truth of existing API specifications. These results demonstrate the benefits of our technique.

Listing 1: Example OpenAPI specification.

```
1  info:
2    title: Conduit API
3  servers:f
4    - url: http:/localhost:3000/api
5  paths:
6  /articles/{id}:          /* path item */
7      get:                 /* HTTP method */
8        parameters:
9          - name: id
10           in: path
11           required: true
12           schema: Integer
13           example: 2
14       responses:
15         200:
16           description: OK
17           content:
18             application/json:         /* MIME */
19               schema:
20                 ref: '/schemas/SingleArticleResponse'
```

The contributions of this work are:

- A first-of-its-kind approach for carving API test cases from UI paths that enables API-level testing for web applications, irrespective of the frameworks they use.
- A novel technique for inferring API specifications for web applications that use RESTful services.
- An implementation of the techniques in a tool called APICARV that is publicly available [29].
- Empirical assessment of APICARV, demonstrating the tool's effectiveness and the benefits of carved tests.

II. BACKGROUND AND MOTIVATING EXAMPLE

REST APIs [1] are typically described in a specification (e.g., in OpenAPI [2] format, previously known as Swagger) that lists the available service operations, the input and output data structures for each operation, and the possible response codes. Listing 1 shows a snippet of the OpenAPI spec for the REST API of a web application called `realworld` [30] (one of the applications used in our evaluation). The spec lists path items (under `paths:`), where a *path item* consists of a resource path (also referred to as "API endpoint") together with one or more HTTP methods (or "Operations"). The path item illustrated in Listing 1 shows the resource path (line 6), the HTTP method (line 7), the parameters specification (lines 8–13), and the response specification (lines 14–20). The response specification lists the status code (line 15) and the response data format (line 18) and the structure (lines 19–20). The structure definition contains a reference to a schema defined elsewhere in the document (omitted here).

The resource path `/articles/{id}` (line 6) is specified as a URI template [31], with path parameter `id`. Such a resource path describes a range of concrete URIs via parameter expansion. A concrete URI instance in an HTTP request targeting that endpoint contains an integer value for `id` (e.g., `/articles/2`). More generally, a path item can contain four kinds of parameters—path, query, cookie, and header. Path and

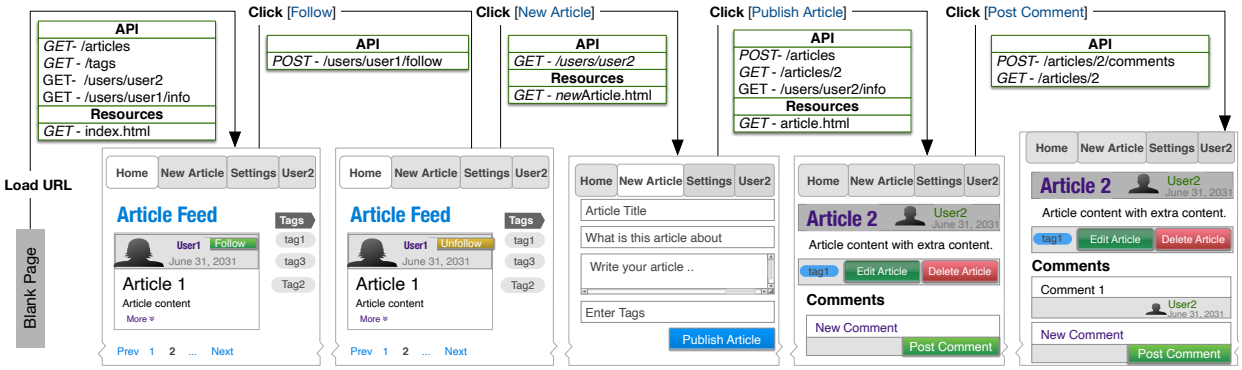


Fig. 1: Example illustrating a sequence of UI actions and states along with the API calls that are triggered by UI events.

query parameters are related to the URI, whereas header and cookie parameters are associated with HTTP request headers.

Figure 1 shows a UI test path for the `realworld` [30] web application. The test performs five UI actions that navigate through different application states. Each action exercises a specific functionality. For example, "`Click[follow]`" invokes the functionality to *follow* a given user. The figure also shows the server-side APIs invoked by the browser for each UI action. The UI states are then updated based on the server response. For instance, "`Click[follow]`" invokes the API "`POST[/users/user1/follow]`" and the UI state is updated, to show that "follow user" succeeded.

From the perspective of functional testing of the server-side APIs of a web application, the UI actions and the API calls invoke the same functionality and, therefore, would have the same code coverage and fault-detection abilities. However, invoking the APIs directly, instead of going through the UI layer has advantages: API calls exercise the service-side functionality much more efficiently and are less prone to the brittleness usually associated with UI tests [32], while exercising the APIs in the manner they are invoked from the UI. Thus, carved API tests can be convenient for developers to use in the course of their development activities. This is not to say that carved API tests are an alternative to, or replacement for, the UI tests. UI testing has an important role to play in covering end-to-end flows through all the application tiers; however, such testing is more suitable for system-level or acceptance testing in practice, and less so for supporting developers in their server-side development activities. Our first goal in this work, therefore, is to enable API-level testing such that it is universally applicable for all web applications irrespective of the web frameworks they use.

The second goal of our work is to infer an API specification, such as the one illustrated in Listing 1, automatically for the server-side APIs of a web application. The inferred specification documents the APIs and can also be used as input to automated API testing tools (e.g., [6], [7], [8], [10], [12]). API specification inference is applicable to web applications that implement RESTful APIs. Although API specifications could also be inferred for other types of web applications and could serve as useful documentation of server-side APIs, they would be less effective as inputs to automated API testing tools.

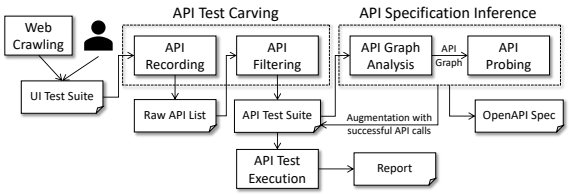


Fig. 2: Overview of our technique APICARV.

The core challenge in specification inference is how to compute resource paths with path parameters accurately (e.g., the `{id}` component of resource path `/articles/{id}`). The concrete URI instances in the requests observed at runtime contain integer values for `id`, such as `/articles/2`. The technique has to determine which segments of concrete URIs represent path parameters. Moreover, a resource path can have multiple path parameters, which adds to the complexity of the problem. In the next section, we present a dynamic-analysis-based carving technique for addressing these challenges.

III. APPROACH

Figure 2 presents an overview of our technique called APICARV. The input is a suite of UI test cases for a web application—the test cases could be automatically generated (e.g., created via automated web crawling) or implemented by developers. The output consists of an API-level test suite, along with a test-execution report, and for applications that use RESTful APIs, an OpenAPI specification describing the server-side APIs of the web application. The API test suite is composed of carved test cases that are augmented with API calls made during specification inference. The test-carving phase of the technique involves API recording and API filtering. The specification-inference phase constructs an API graph from the API test suite, and analyzes the graph to create an OpenAPI specification. A key step during specification inference is *API probing*, which attempts to expand the set of resource paths observed during UI test execution and discover additional information for creating more accurate specifications as well as augmenting the carved test suite. Next, we describe the two phases of the technique in detail.

A. API Test Carving

APICARV performs API test carving in two steps. In the first step, API recording, the technique monitors API calls that

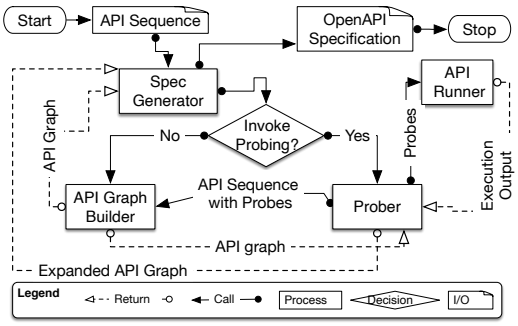


Fig. 3: The specification-inference flow (`InferSpec`).

are triggered through the execution of the UI test suite and logs the raw API calls. To record API calls, we add network listeners to the browser executing the UI tests, which capture the raw outgoing and incoming HTTP traffic. As Figure 1 illustrates, a UI action can result in multiple API calls being executed, e.g., `Click[Publish Article]` triggers one POST and three GET requests. These requests, together with their corresponding responses, are logged during API recording.

In the second step, API filtering, the technique applies a series of filters—operation filter, status filter, and MIME filter—to the raw API calls to remove the calls that are irrelevant for API test and specification carving. The *operation filter* is based on HTTP method checking and is designed to omit methods that are unrelated to resource manipulation. This filter removes all calls with HTTP methods TRACE and CONNECT. The *status filter* checks the response status codes and excludes calls with unsuccessful requests, indicated by 4xx and 5xx response codes. Finally, the *MIME filter* checks the MIME type of the response payload and retains only those calls whose response payloads contain JSON or XML data (i.e., MIME types `text/json` or `text/xml`). For example, the resource-related API calls shown in Figure 1, which are irrelevant for API-level testing, are removed during filtering.

In the implementation of our technique, the filtering step is configurable. The three filters described here proved to be adequate for our experimentation. However, the user can configure filtering to prevent omission of certain requests considered essential for API testing or provide custom filters to omit additional types of API calls not covered by the three filters. Filtering configuration may also be needed based on web application characteristics; e.g., the MIME filter would be relevant if the application consists of RESTful APIs.

The output of the filtering step consists of sequences of API calls from which the carved API test suite is created.

B. API Specification Inference

As discussed in II, the core problem in specification inference that our approach addresses is computing path parameters for resource paths. The technique has to detect the path components of concrete URI instances that represent parameters, while handling paths with multiple parameters and compensating for server-side state changes as a result of UI actions that can potentially impact server responses for URIs.

Algorithm 1: API graph construction

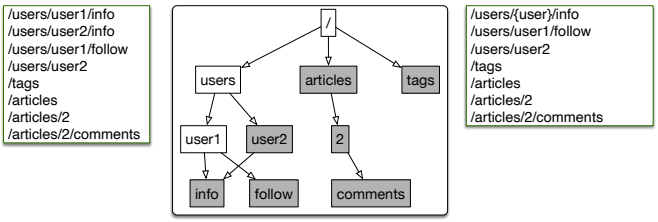
```
1  Function BuildAPIGraph:
       Input: apiset ← [A_1 ... A_n]                    /* Set of API Calls */
       Init: G ← φ                                      /* API Graph for the given set of API calls */
2      foreach A ∈ apiset do
3          path ← A.Rq.URL.path
4          SegArray ← path.split()                      /* split path into segments */
5          parent ← root                                /* a dummy starting node */
6          foreach Seg_i ∈ SegArray do
7              parentPath ← join(Seg_0, ..., Seg_{i-1})
8              v ← φ                                    /* path parameter inference later */
9              if i = SegArray.size then
10                 end-point ← True
11             else
12                 end-point ← False
13             end
14             pathSeg ← (Seg_i, i, parentPath, SegArray.size, endpoint, v)
15             segExists ← for-all ν_s ∈ N AreEqual(pathSeg, ν_s)
16             if segExists then
17                 G.addEdge(parentNode, ν_sim)
18                 parentNode = ν_sim
19             else
20                 G.addNode(pathSeg)
21                 G.addEdge(parentNode, pathSeg)
22                 parentNode = pathSeg
23             end
24         end
25     end
26     return G
27 end
28 Function AreEqual (ν_1, ν_2):
       Output: True or False
29     if (ν_1.n ≠ ν_2.n) ∨ (ν_1.d ≠ ν_2.d) then
30         return False                                 /* different name or path index */
31     end
32     if ν_1.p = ν_2.p then
33         return True                                  /* same name, path index, and parent path */
34     end
35     if IsEndPoint(ν_1) ∧ IsEndPoint(ν_2) then
36         return CompareResponses(ν_1.l, ν_2.l)
37     else
38         return False                                 /* different parent path */
39     end
40 end
```

Figure 3 presents a flow chart, `InferSpec`, illustrating specification inference. `InferSpec` takes as input the API sequences created by API carving and produces as output an API specification. It builds an API graph to represent the discovered resource paths and analyzes the graph to create the API specification. `InferSpec` also analyzes the graph to generate API probes (i.e., concrete API requests) that are executed against the application to discover additional valid API calls that are missing in the initial set of API sequences.[2] This step is intended to address the incompleteness of the initial API sequences and, thereby, improve the accuracy of the inferred API specification. As an additional benefit, the successful probes can be used for augmenting the carved API test suite, potentially increasing its coverage.

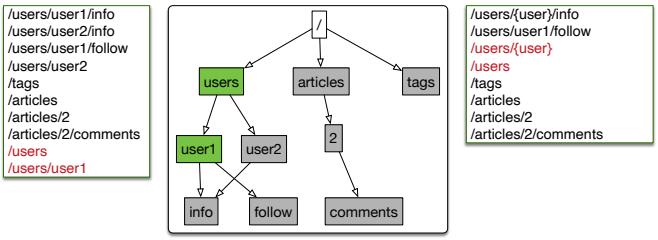
1) API Graph Construction: Algorithm 1 presents the algorithm for building the API graph. Before describing the algorithm, we introduce some terminology.

Definition 1 (**Path Segment**). Given a URI U, a *path segment* ν is a tuple (n, d, p, e, l, v), where n is the segment string, d is the index of the segment in U, p is the parent path for ν, e is a boolean indicating whether ν is the final segment of U (and, therefore, an API endpoint), l is the response payload (if e is true), and v is the path parameter inference result for ν.

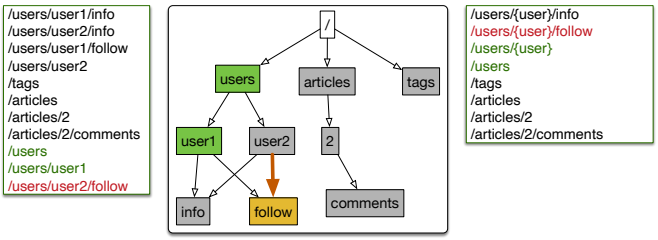
[2]In the implementation of the technique, API probing can be limited by upper bound on exploration time or number of probes executed.



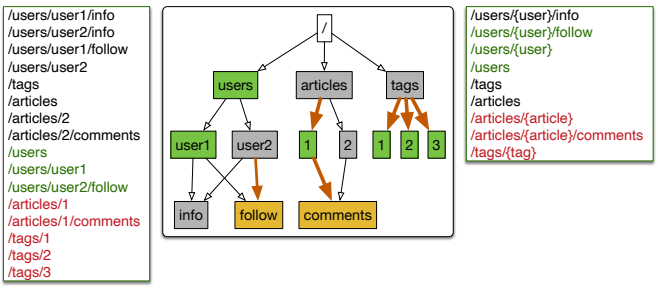
(a) API calls carved from the UI execution



(b) Probing Stage 1: probes for intermediate nodes



(c) Probing Stage 2: probes from bipartite analysis



(d) Probing Stage 3: probes from response analysis

Each subfigure shows the API graph (middle) built from API calls (left) and the inferred specification (right). The color coding of API calls (spec paths) indicates calls recorded (paths created) during UI navigation (black) and probes (paths) created in the previous stage (green) and the current stage (red). The color coding of nodes illustrates nodes created after UI navigation (gray), nodes with responses discovered via probing (green), and nodes with extra responses because of probing (yellow). The edge colors highlight edges created by probes in the previous stage (green) and the current stage (red).

Fig. 4: Illustration of specification inference.

Definition 2 (API Graph). An *API graph* $\mathcal{G} = (\nu_r, \mathcal{N}, \mathcal{E})$ is a directed acyclic graph, where ν_r is the dummy root node of the graph, $\mathcal{N}$ is a set of nodes, and $\mathcal{E}$ is a set of edges. Each node in $\mathcal{N}$ is a path segment and a pair of consecutive segments in a URI is connected by an edge in $\mathcal{E}$.

Definition 3 (Graph Path). A *graph path* in an API Graph is a sequence of path segments $(\nu_r, \ldots, \nu_x)$ that connects the root node ν_r to any graph node ν_x. A complete path is a path from ν_r to a node where $\nu.e$ is true.

An API graph is constructed for a set of URIs (extracted from API calls). To illustrate, consider the API graphs shown in Figure 4. Each API graph represents the URIs shown to the left of the graph. A graph node, except the root node, represents one or more segments from the URIs, and each complete path represents a URI.

Function `BuildAPIGraph` (lines 1–27) of Algorithm 1 iterates over a given set of API calls ($\mathcal{A}$) and builds an API graph by parsing each request URI into a path in the graph. For each URI, the algorithm splits the URI into segments and then builds a path segment for each segment (lines 7–14). If a path segment ν is not similar to any of the existing path segments in the graph, ν is added to the graph (lines 15–23).

The similarity of two path segments is determined by the function `AreEqual` (lines 28–40), which first compares the names and path indexes of the two segments (line 29). If either of these do not match, the path segments are considered to be different. For example, as shown in Figure 4, each string segment in a URI has its own node in the graph. If the names and path indexes match, the function next compares the parent paths of the segments (using string comparison) and considers the segments to be equivalent if the parent paths match (lines 32–34). Otherwise, if the segments represent endpoints, the function `CompareResponses` is called to determine segment equivalence (lines 35–36). Note that a response object is available for a path segment only if there exists an API call that ends at the segment, making it an endpoint.

`CompareResponses` (not shown in Algorithm 1) relies on the structural similarity of responses instead of matching the entire responses. For a response with JSON or XML data, it ignores the *values* and builds a tree with *keys* in the data. It then asserts the structural similarity of the trees to determine response similarity. For example, consider the requests [`GET /users/user1/info`] and [`GET /users/user2/info`] in Figure 4) with responses `{"id":1, "name":"user1", "role":"user"}` and `{"id":2, "name":"user2", "role":"user"}`. To compare these two responses, the technique builds trees using the keys `[id, name, role]` and invokes a tree-comparison technique (APTED [33]) to check their equivalence.

2) API Specification Generation: Algorithm 2 presents the steps involved in generating API specification from the API graph. Our goal in specification inference is to make the specification precise in terms of the number of path items for each API endpoint. An ideal specification should have exactly one path item describing an API endpoint; URI templates with path parameters make it possible to do so.

The algorithm first merges leaf nodes in the API graph (line 2). The function `MergeLeafNodes` (lines 15–23) performs response comparison to determine whether two nodes with different names belong to the same API endpoint. In addition, the algorithm makes use of the graph structure by getting paths that reach the same endpoint node in the API graph (lines 24–37). Finally, after computing a list of URIs that belong to similar endpoint nodes in the API graph, the technique performs a simple path-index-based match per URI segment to extract a template (lines 5–11).

For example, in Figure 4a, for the leaf node `info`, `GetGraphPaths` returns two graph paths for URIs `/users/user1/info` and `/users/user2/info`, which the

Algorithm 2: Generating API specification from API graph

```
1  Function ExtractOpenAPI:
       Input: 𝒢                          /* API Graph after path variable inference */
       Output: uriTemplates ← ϕ
2      𝒢 ← MergeLeafNodes(𝒢)
3      foreach do ν ∈ 𝒢
4          if ν_i.e = True then
5              paths ← GetGraphPaths(ν_i)
6              if paths.size > 1 then
7                  template ← getURITemplate(paths)
8              else
9                  template ← paths[0]
10             end
11             uriTemplates.add(template)
12     end
13     return uriTemplates
14 end
15 Function MergeLeafNodes:
       Input: 𝒢                          /* API Graph for the given set of API calls */
16     foreach ν_i ∈ {ν_n} do
17         foreach ν_j ∈ {ν_n} do
               /* Assign a variable when nodes have matching responses */
18             if (ν_i.e=True) ∧ (ν_j.e=True) ∧ (CompareResponses(ν_i,
                 ν_j)=True) then
19                 ν_i.v = ν_j.v = variableMap.get()
20         end
21     end
22     return 𝒢
23 end
24 Function GetGraphPaths:
       Input: 𝒢, ν_x                     /* An API Graph and a node in it */
       Output: paths ← ϕ
25     foreach ζ_i ∈ 𝒢.getPathsto(ν_x) do
26         path ← ϕ
27         foreach ν_i ∈ {ν_n} do
28             if ν_i.v != ϕ then
29                 path.add(ν_i.name)
30             else
31                 path.add(ν_i.v)      /* v is set by MergeLeafNodes */
32             end
33         end
34         paths.add(path)
35     end
36     return paths
37 end
```

technique considers equivalent and extracts the template `/users/{user}/info` with path parameter `{user}`.

For the example in Figure 4b, the graph paths for URIs `/users/user1` and `/users/user2` end at different segments. However, `MergeLeafNodes` performs response comparison to determine that these segments are equivalent and sets a variable to represent the path parameter (line 19 of Algorithm 2). Then, `GetGraphPaths` uses that variable and returns the string `/users/{user}` for both URIs. Finally, that returned string is used as the template with path parameter `{user}`. We use variable name `user` here for readability; our implementation creates variable names such as `var0`.

3) API Graph Expansion via Probing: The API graph created from the set of API calls seen during UI navigation is limited by the completeness of UI tests, which can affect the precision and completeness of the inferred API specification. To address this, APICARV expands the initial API graph via systematic API probing.

The technique creates four types of probes: intermediate, bipartite, response, and operation. Intermediate and bipartite probes are built via API graph analysis, response probes are based on HTTP response analysis, and operation probes aim to discover unseen operations for known API endpoints. After building probes, the technique sends them to the server using a scheduling algorithm that avoids data dependencies. The successful probes (i.e., probes with response codes other than 4xx or 5xx) are used for enhancing the API graph and augmenting the API test suite. `InferSpec` uses the expanded API graph to generate a potentially more accurate API specification.

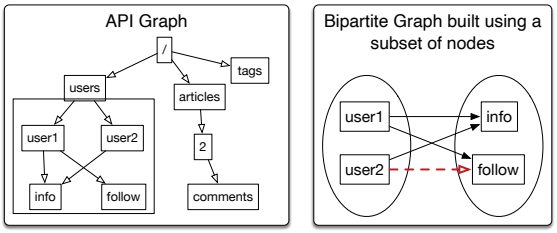


Fig. 5: Bipartite analysis for API probe generation.

Intermediate probes: These probes are created for API graph nodes that do not have an associated server response (i.e. $\nu.e$ is false). For example, in Figure 4b, the probes `/users` and `/users/user1` are intermediate probes built for the nodes `users` and `user1` that do not have an associated response. In this case, the two endpoints are indeed valid. As a result, `InferSpec` adds a new path item `/users` and computes path variable `user` for the existing path `/users/user2`, which it replaces with the template `/users/{user}`.

Bipartite probes: These probes are generated by building a bipartite graph from join nodes (i.e., nodes that have more than one predecessor) in the API graph. To illustrate, consider the example in Figure 5, where join node `info` has two predecessors (`user1` and `user2`). For this node, the technique constructs the bipartite graph shown in the figure: the left part of the graph contains all predecessors of the join node and the right part contains all successors of nodes in the left part. The technique then computes missing edges that would make the bipartite graph complete, i.e., each node on the left is connected to each node on the right. In this example, one missing edge makes the bipartite graph complete. From this analysis, probe `/users/user2/follow` is generated. As shown in Figure 4c, this new probe lets the technique infer the new path variable `user` and convert concrete resource path `/users/user1/follow` to path template `/users/{user}/follow`, thereby improving the specification.

Response probes: Response probes are generated by analyzing the server responses for existing API calls. For each response object, the technique builds probes from keys and values extracted from the response. Suppose the response for `GET /tags` is `[{ id: 1, name: tag1, author: user1}, { id: 2, name: tag2, author: user1} ..]`. Using this response, we build probes such as `/tags/1`, `/tags/id`, `/tags/tag2`, `/tags/author`. As shown in Figure 4d, by analyzing the `articles` object, we build probes `/articles/1/comments` and `/articles/1`, which result in inference of path templates `/articles/{article}` and `/articles/{article}/comments`. Similarly, response analysis of `tags` object helps us infer `/tags/{tag}`.

Operation probes: Operation probes are generated by analyzing API calls based on coverage of HTTP methods per known API endpoint. We consider seven HTTP operations—

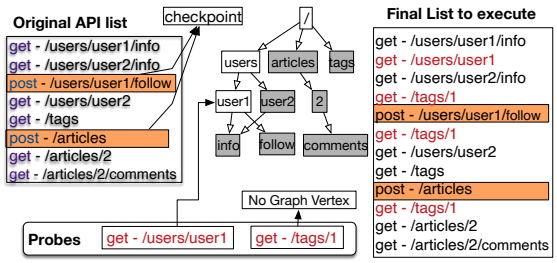


Fig. 6: Example for illustrating probe scheduling.

GET, POST, PUT, PATCH, OPTIONS, HEAD, and DELETE—in our analysis. For example, if the existing set of API calls contains `GET /tags/1` and `PATCH /tags/1`, we generate five probes for the endpoint, each covering one of the remaining HTTP operations (e.g., `DELETE /tags/1`).

Probe Scheduling: HTTP requests can cause server-side state updates and, in general, the server response for a request can vary based on other requests. Moreover, the resources corresponding to a URI could be dynamic and only available in certain server-side states. Therefore, API probing should be performed at appropriate server states; our technique achieves this via probe scheduling, based on API graph analysis.

For each probe, we first check if the URI has a corresponding endpoint node in the graph. Consider the example in Figure 6. Node `user1`, which is the endpoint node for URI `/users/user1`, already exists in the graph, whereas the corresponding node for `/tags/1` does not exist. If the endpoint node for a probe exists, we schedule the probe immediately before the last request in the original list whose URI includes the segment/node. If the endpoint node does not exist, we schedule the probe after each checkpoint request. A *checkpoint request* is an HTTP request that can change the server-side state. We define two types of checkpoints: cookie-based and operation-based. Cookie-based checkpoints are the HTTP requests for which the server responds with a `set-cookie` field. Operation-based checkpoints correspond to HTTP requests capable of modifying resources, i.e., HTTP methods PUT, POST, DELETE, and PATCH. In Figure 6, the two POST requests are checkpoint requests. As the final list in Figure 6 shows, `GET /users/user1` is scheduled only once, immediately after the node is discovered in the graph, whereas `GET /tags/1` is scheduled three times (corresponding to three potential server-side states), once before any checkpoint and once each after the two checkpoints in the original list. After the probes are executed, we keep only one instance of a successful probe in cases where multiple instances succeed.

IV. Implementation

We implemented our technique in a tool called APICARV. We use Crawljax [34] to generate [35] UI test cases automatically. The API recorder module uses the Chrome Devtools Protocol [36] along with Selenium [37] to instrument the browser during UI test execution to record API calls. Our implementation and experimental dataset are publicly available in a replication package [29].

TABLE I: Web applications used in the evaluation.

Application	Framework	# API Endpoints	# Operations	LOC
booker	Spring-boot, ReactJS	15	24	8K
ecomm	Spring-boot	21	22	6K
jawa	Spring-boot, AngularJS	5	8	20K
medical	Spring-boot, VueJS	20	28	5K
parabank	Spring-mvc, AngularJS	27	27	60K
petclinic	Spring-boot, AngularJS	17	36	39K
realworld	Express, NextJS	12	19	12K
Total		117	164	150K

V. Empirical Evaluation

We investigated the following research questions in the evaluation of APICARV.

- RQ_1: How do carved API tests compare with UI tests in terms of code coverage and execution efficiency?
- RQ_2: How effective is APICARV in generating OpenAPI specifications?
- RQ_3: Do carved API tests improve the coverage achieved by automatically generated API test suites?

A. Experiment Setup

We performed the evaluation on seven open-source web applications; Table I lists the applications and their characteristics. All of the applications implement RESTful APIs for their services and have OpenAPI specifications available, which serve as ground truth for measuring the accuracy of the inferred API specifications.

For UI test generation, we configured Crawljax to run for 30 minutes. We also created 14 manual tests for three subjects (`booker`, `medical`, `ecomm`), which required dedicated action sequences and input data. Thus, our evaluation uses automatically generated and developer-written UI test cases.

For investigating RQ_3, we used two popular automated test generators for REST APIs—EvoMaster [26] and Schemathesis [27]. EvoMaster can be used in white-box and black-box modes; in the white-box mode, it is applicable to REST APIs implemented in the Java language. For our study, we used EvoMaster in its black-box mode so that it can be applied to non-Java API implementations in our subjects. A recent empirical study [38] showed these two tools to be the top-performing tools, in terms of code coverage achieved, among the black-box testing tools for REST APIs. We configured EvoMaster to run for one hour; for Schemathesis, we used its default configuration settings. We ran each tool 10 times to account for randomness and report coverage data averaged over the 10 runs. To measure code coverage, we used JaCoCo [39] for Java-based APIs and Istanbul [40] for JavaScript-based APIs.

B. Quantitative Analysis of APICARV Stages

Before discussing our results on the research questions, we present empirical data on different stages of APICARV and provide a quantitative analysis of the stages. Table II presents data about the filtering, probing, and test-generation stages.

Columns 2–3 of the table show the number of API calls available after recording and filtering, and highlight the importance of filtering: i.e., a large proportion of the raw API calls recorded get filtered out. These calls basically retrieve

TABLE II: Statistics about different analysis stages in APICARV runs on the subject applications.

	API Filtering		Probing				Generated Test Suites							
							Carver				Carver + Prober			
	Recorded	Filtered	Generated	Executed	Succeeded	Checkpoints	Paths total	Paths success	Requests	Time (s)	Paths total	Paths success	Requests	Time (s)
booker	3610	613	529	85295	57	203	14	10	443	21	24	20	500	21
ecomm	7838	1187	440	4906	4	18	61	60	1175	21	61	60	1179	15
jawa	1568	198	60	279	13	7	9	4	110	6	18	13	123	6
medical	315	122	1277	39309	17	32	24	23	117	15	26	25	134	17
parabank	13072	574	694	43833	26	68	25	23	572	125	29	27	598	124
petclinic	1536	294	1399	5144	102	42	20	20	290	5	50	50	392	7
realworld	1471	398	7510	72259	225	9	62	36	365	79	116	91	590	103
Total	29410	3386	11909	251025	444	379	215	176	3072	273	324	286	3516	294

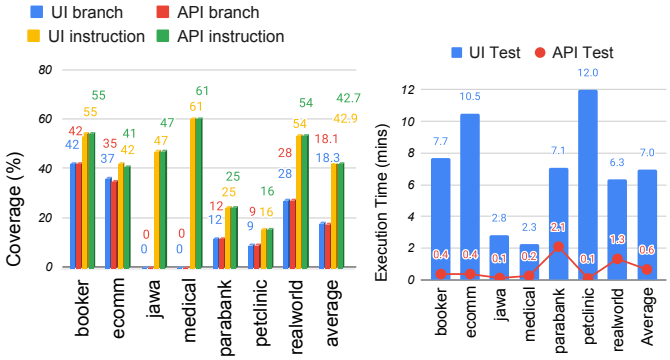
resources related to UI rendering in the browser and can be ignored for testing the functionality of server-side APIs. On average, over 88% of the raw API calls belong to the category of irrelevant calls. The proportion of such calls ranges from over 72% (for `realworld`) to over 95% (for `parabank`). Thus, API filtering is an important component of APICARV; moreover, as discussed in Section III-A, the filtering component can be configured to be more strict (removing more of the raw API calls) or less stringent (removing fewer calls).

Columns 4–7 present information about the probing stage: probes generated, probes executed, and checkpoints in the filtered API list. On average, the number of probes generated is over three times the number of filtered API calls, and the number of probes executed is 21 times the number of generated probes. Recall from the discussion of probe scheduling in Section III-B that some probes are scheduled for multiple executions based on occurrences of checkpoints in the initial API list. The number of generated probes varies considerably, ranging from 0.3 times the initial API calls (for `jawa`) to almost 19 times the initial API calls (for `realworld`). A similar large variation can also be seen in the number of probes executed. Finally, 444 probes were successful and are added to API test suite generated at the end of probing.

Columns 8–15 of Table II present data about test generation, broken down by tests created during carving and probing. It can be seen that the total number of successful paths, which are the number of valid resource paths discovered, increases from 176 in the Carver test suite to 286 in the Prober test suite. The Prober is, thus, able to discover 110 additional valid resource paths across the applications. These 110 path invocations come at the cost of only 21 seconds. In other words, the Prober test suite is able to successfully exercise 62.5% more paths with only 7.6% increase in test-execution time.

C. RQ_1: Coverage Rates and Execution Efficiency of Tests

Figure 7a presents coverage rates for UI tests and carved API tests. As the data illustrate, the coverage is identical for all applications, except `ecomm`, for which instruction and branch coverage of API test cases are marginally lower (by 1% and 2% respectively). We suspect that this difference may have been due to API filtering. On average, carved API test suites covered 18.1% branches and 42.7% instructions, which is 0.2% less than the coverage achieved by the UI test suites. Thus, overall, the carved API tests perform very well in matching the coverage rates of UI test cases.



(a) Code coverage (b) Execution time

Fig. 7: Coverage rates and execution times of UI tests and carved API tests.

In terms of execution efficiency, however, there is a big difference between the two types of test cases, as Figure 7b shows. On average, the UI test suites took seven minutes to run, whereas the API test suites ran in about 0.6 minutes only—more than 10x improvement in execution efficiency. The biggest improvement occurs for `petclinic`, for which the UI test suite took 150 times longer to run than the API test suite. Even with the smallest improvement, which occurs for `parabank`, the API tests executed over 3x faster than the UI tests (2.1 minutes versus 7.1 minutes, respectively).

> The carved API tests match the coverage achieved by UI tests while executing significantly (10x) faster than UI tests. Thus, carved API tests can be employed for improving test execution efficiency, without incurring loss in coverage of server-side code.

D. RQ_2: Accuracy of Inferred OpenAPI Specification

Goals and Measures. To measure the effectiveness of APICARV in inferring API specifications, we compute precision, recall, and F_1 scores for the generated OpenAPI specification (S_{gen}) against the existing OpenAPI specification, considered the ground truth (S_{gt}), for each subject. We compute these scores for resource paths and operations (HTTP methods) defined on resource paths, and for the specification generated from the API graphs computed after carving and probing. Precision and recall are computed in the usual way, based on true positives, false positives, and false negatives. A path/operation is considered true positive if it occurs in both S_{gen} and S_{gt}, false positive if it occurs in S_{gen} but not in S_{gt}, and false

TABLE III: Precision, recall, and F1 scores achieved for API specification inference.

	Path			Operation				
Tool	Pr	Re	F_1	Pr	Re	F_1	Pr*	F_1*
Carver	1.00	0.49	0.32	0.85	0.46	0.28	1.00	0.31
Carver+Prober	0.98	0.56	0.35	0.48	0.54	0.25	0.95	0.34

negative if it occurs in S_{gt} but not in S_{gen}. F_1 score is the harmonic mean of precision and recall. In addition to these metrics, we measure *duplication factor* for S_{gen}. A duplication occurs when multiple paths/operations in S_{gen} correspond to the one path/operation in S_{gt}. We map paths in S_{gen} to paths in S_{gt}, and compute duplication factor as (# mapped paths in S_{gt} / # mapped paths in S_{gen}). The computed value ranges from 0 to 1, with higher values indicating less duplication (the value 1 means there is no repetition of API endpoints in S_{gen}). The presence of duplication causes S_{gen} to contain redundant paths/operations that can be combined.

Results and Analysis. Table III presents the precision, recall, and F1 scores for specification inference. In terms of resource paths, APICARV achieves 100% precision for specifications created after carving and 98% precision after probing (Column 2). The recall after the carving phase is 49%, which the probing phase improves to 56%—a gain of 14% (Column 3). The probing phase is intended to address incompleteness in the API calls observed during UI navigation; the result shows that it achieves that to some degree and with only a small reduction in precision. The overall recall at 56% is somewhat low, which is a consequence of the incompleteness inherent in dynamic analysis. This could be addressed via improvements in crawling or providing higher coverage UI test suites as input to APICARV. This concern is orthogonal to APICARV's core specification-inference and test-carving techniques.

In terms of operations, the results for recall (Column 6) after the carving phase is 46%, which the probing phase improves to 54%—a gain of 17%. The precision value for operations is high (85%) after carving, but there is a significant drop to 48% after probing (Column 5). Upon closer inspection, we found that this is caused by operation probes, specifically the probes with HTTP methods `OPTIONS` and `HEAD`; these requests are not handled correctly in any of the subjects. Ideally, an `OPTIONS` request should provide available operations for an API endpoint and the corresponding specification for the endpoint should contain `OPTIONS` as an operation. In all of our subjects, while the server returns a success status (200 code) for an `OPTIONS` request, the corresponding operation is not documented in the specification. We consider this to be a specification inconsistency with respect to application behavior; on ignoring this inconsistency, APICARV achieves 95% precision for operations as well, shown as Pr* in Table III (Column 8).

> APICARV achieves high precision in inferring resource paths and operations. The probing phase of APICARV increases the recall and F1 scores, while not causing a significant reduction in precision.

TABLE IV: Endpoints inferred, path/operation duplication found, and operation inconsistencies detected.

	Endpoints		Duplication				Operation	
	Inferred		Path		Operation		Inconsistencies	
	carver	car+pro	carver	car+pro	carver	car+pro	carver	car+pro
booker	8	10	0.89	0.91	0.92	0.94	0	21
ecomm	13	13	0.81	0.81	0.82	0.82	11	14
jawa	2	2	1.00	1.00	1.00	1.00	0	2
medical	15	16	0.88	0.89	0.89	0.90	9	17
parabank	9	9	1.00	1.00	1.00	1.00	0	12
petclinic	8	12	0.80	0.67	0.94	0.67	5	18
realworld	4	5	0.57	0.56	0.57	0.56	0	18
Average/Total	59	67	0.85	0.83	0.88	0.84	25	102

A manual analysis revealed that the path and operation precision drops from 1.0 to 0.98 and 0.95 because of one API endpoint found through probing in `realworld`. We verified that the resource path is indeed valid and provides a health-check for the service despite being absent in the specification, a potential inconsistency. Table IV shows the operation inconsistencies that we found per subject. The inconsistencies exposed by the carver are particularly interesting because these `OPTIONS` and `HEAD` requests are actually being used by the client—the application UI layer running in the browser—to communicate with the server. Recall that the carver uses only the requests captured during UI navigation. For example, the UI client of the `ecomm` application uses the `OPTIONS` operation on 11 API endpoints for server communication. These inconsistencies indicate room for potential improvements in the specifications, in particular, by documenting the `OPTIONS` HTTP method for API endpoints.

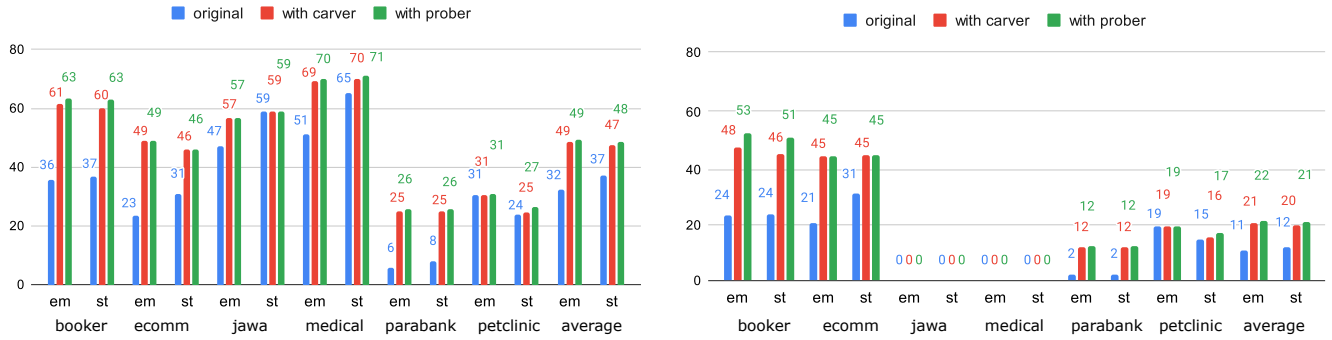
Columns 4–7 of Table IV show the duplication factor computed for the specification generated after the carving and probing phases. It can be seen that the duplication factor does not vary significantly for six of the subjects. Path and operation duplication drops to 0.67 from 0.8 and 0.94, respectively, for `petclinic` because of the challenge in determining similarity of responses (Algorithm 2 lines 15–23). Recall that we use tree-based comparison to determine response similarity and, in the case of petclinic, the server provides responses that are structurally dissimilar based on the back-end data differences.

Endpoints covered (Columns 2–3 of Table IV) improves for four of the seven subjects, with the largest increase of 50% occurring for `petclinic`. Overall, endpoint coverage increases from 59 to 67, for 14% increase, which is reflected in the path recall values (Column 3 of Table III) as well.

> APICARV can detect potential inconsistencies between API implementations and specifications, and could be leveraged for improving specifications.

E. RQ$_3$: Augmentation Effectiveness of Carved API Tests

Goals and Measures. With RQ$_3$, we investigate the usefulness of carved API tests in enhancing the coverage rates achieved by EvoMaster [26] and Schemathesis [27]. Specifically, we measure instruction and branch coverage of the test suites generated by those tools; then, we augment the test suites in two steps, by adding the carved API tests and the successful



(a) Instruction coverage

(b) Branch coverage

Fig. 8: Augmentation effectiveness of carved tests: coverage rates of test suites generated by EvoMaster (em) and Schemathesis (st) before augmentation (original) and after augmentation with carved tests and probes.

probes to the test suites, and measuring coverage gains in each augmentation step.

Results and Analysis. Figure 8 presents the results for RQ_3. It shows the instruction and branch coverage rates for the original API test suites generated by EvoMaster and Schemathesis and the two augmented test suites. Overall, our augmentation causes coverage increases in most instances, with a few exceptions (e.g., there are no instruction coverage gains for `jawa` with Schemathesis). In terms of instructions, on average, the coverage of EvoMaster test suite increases from 32% to 49%, for a coverage gain of 52%; for Schemathesis, coverage increases from 37% to 48%, for a coverage gain of 29%. For branch coverage, augmentation has a bigger effect because of the low coverage rates of the original test suites. For EvoMaster, branch coverage gain is 99%, increasing from 11% to 22%. For Schemathesis, branch coverage gain is 75%, increasing from 12% to 21%. For both types of coverage, the gains for `booker`, `ecomm`, and `parabank` are substantial.

Moreover, additional coverage from probes, on top of the gains from carved tests, occurs in several instances. For example, the probes provide a considerable increase in branch coverage for `booker`—48% to 53% for EvoMaster and 46% to 51% for Schemathesis.

> APICARV can significantly increase coverage achieved by EvoMaster and Schemathesis and, thus, can effectively complement such tools. The probing stage of APICARV can provide small additional gains on top of the gains from API tests carved from UI paths.

To understand how carved API test suites can complement API testing techniques, we performed an in-depth analysis of the differences in code coverage achieved by the testing tools and APICARV. Our analysis revealed two interesting high-level scenarios where carving API test suites from end-to-end UI test suites could improve the overall effectiveness of API-level testing of web applications.

First, generating appropriate test data to cover API endpoints is a challenging aspect of API fuzzing, and carved API test suites can be leveraged to cover certain endpoints that require specific test data. An example of such a scenario

```
/visits/{visitId}:
  get:
    parameters:
      -name: visitId
       in: path
```

```
public ResponseEntity getVisit(Integer visitId) {
    Visit visit = this.clinicService.findVisitById(visitId);
    if (visit == null) {
        /* Covered by ApiCarv, Schemathesis and Evomaster */
        return new ResponseEntity<>(HttpStatus.NOT_FOUND);
    }
    /* Covered by ApiCarv through probing */
    return new ResponseEntity<>(visitMapper.toVisitDto(visit), ↩
        HttpStatus.OK);
}
```

Fig. 9: Example of an endpoint and the associated service code (from `petclinic`) that requires specific test data.

```
/user/signUp:
  post:
    params: {in: body, schema: {"user": string, "pass": string}}
    responses: {200: {"status": string}}

/user/signIn:
  post:
    params: {in: body, schema: {"user": string, "pass": string}}
    responses: {200:{"status": string, "token": string}}

/cart/add:
  post:
    params: {name: token, in : query, schema : string}
```

Fig. 10: Example (from the `ecomm` application) of dependencies between API endpoints.

from `petclinic` is shown in Figure 9 where covering the `/visits/visitId` endpoint requires providing a value for `visitId` that is already present in the application database. In this instance, APICARV leveraged the analysis of API calls observed during the carving phase (derived from the UI test suite) to find a value of `visitId` that covers line 8 of method `getVisit()` and elicits a successful response from the service (`HttpStatus.OK`); EvoMaster and Schemathesis were unable to craft a request with a valid value for `visitId`.

Second, some API endpoints can have dependencies on other API endpoints. Consider the three API endpoints from the `ecomm` application shown in Figure 10. The endpoint `/cart/add` requires a query parameter, `token`, that is generated by the server in response to a call to the `/user/signIn` endpoint. But, to invoke `/user/signIn`, a user must first be registered via the `/user/signUp` endpoint. EvoMaster could invoke `/user/signUp` successfully, but it could not execute the subsequent operations to sign in and add item to cart; Schemathesis could not cover any of these operations. In

contrast, the API test suite carved from the UI test suite of `ecomm` could create a successful `POST /cart/add` request by satisfying these dependencies. The API calls in the carved test suite are constructed by the web application UI, which is developed to adhere to the API specification and valid API invocation sequences. Thus, such dependencies are inherently followed in sequences of API calls made along UI paths, and APICARV captures the call sequences by navigating those paths. The API testing tools, although they attempt to discover meaningful or valid API call sequences, could not generate requests that satisfy the endpoint dependencies in this instance.

Modern web applications are commonly tested in the industry using end-to-end UI test suites, which are often manually created. It is efficient and convenient to develop such UI test suites because of the mature UI testing eco-system and the fact that application business logic is easily translated into a sequence of UI actions on the web interface. API tests carved from such UI test suites can, therefore, contain realistic test data and encapsulate the application business logic in a sequence of API calls. Given these characteristics, carved test suites could effectively complement the API tests generated by API testing tools, such as EvoMaster and Schemathesis.

F. Threats to Validity

Our study may suffer external and internal threats to validity. In terms of external threats, we used seven web applications and two REST API testing tools. Our selection of web applications was constrained to applications that implement RESTful services and have OpenAPI specifications available to serve as ground truth; also, our requirement of measuring code coverage on APIs further constrained the candidate applications. Future evaluation with more and varied web applications will help confirm whether our results generalize. Our selection of REST API testing tools was guided by a recent study [38] that showed EvoMaster and Schemathesis to be the most effective tools, in terms of coverage achieved, among the studied black-box testing tools. Another threat is the use of existing OpenAPI specifications as ground truth. We think this is a reasonable choice for our experiments and we use them with the expectation that they may have some inconsistencies. As for internal threats, there may be bugs in APICARV and our data-collection scripts. We mitigated these threats by implementing automated unit test cases for APICARV and manually checking random samples of our results. We also make APICARV and our experiment artifacts available [29] to enable replication of our results.

VI. Related Work

To the best of our knowledge, our work is the first to propose carving of API-level tests from UI-level test executions. Several papers have explored carving of unit-level tests from system-level executions via code instrumentation (e.g., [23], [24], [25]). Elbaum et al. [23] present a technique for carving unit-level tests from system tests consisting of Java-based code exercising the application end-to-end. Other techniques [24] selectively capture and replay events and interactions between selected program components and the rest of the application, using simplified state representations or they aim [25] at enhancing replay efficiency by mixing action-based and state-based checkpointing. These approaches highlight different advantages of carved tests compared to the original tests, such as their execution efficiency and robustness to program changes. Carved unit tests are shown [23] to be orders of magnitudes faster than the original executions, while retaining most of their fault-detection capabilities. These benefits also motivate our work, and our evaluation demonstrates the significantly superior execution efficiency of carved API tests compared with UI-level tests, with negligible loss in code coverage.

Dynamic specification mining has mostly focused on mining behavioral models of a program from its execution traces (e.g., [41], [42], [43]). These models capture relations between data values and component interactions, to allow for accurate analysis and verification of the software. More relevant to our work are the approaches recently suggested for mining OpenAPI specifications. Several works propose inferring OpenAPI specifications from web API documentation pages. AutoREST [44] infers API specifications from HTML-based documentation via selection of web pages that likely contain information relevant to the specification. It applies a set of rules to extract relevant information from the pages and construct the specification. D2Spec [45] uses machine-learning techniques to extract the base URL, path templates, and HTTP methods from crawled documentation pages. A different approach that uses dynamic information is taken in [46], which generates web API specifications from example request-response pairs. Closest work to ours is SpyREST [47], which intercepts HTTP requests and applies a simple heuristic for identifying path parameters, by considering numeric path items and using regular expression matching. In contrast, our approach infers path parameters via API-graph analysis and API probing. We tried to execute SpyREST for comparison with APICARV's specification inference, but its service failed to work.

VII. Conclusion and Future Work

We presented APICARV, a first-of-its-kind technique and tool for carving API tests and specifications from UI tests. Our evaluation on seven open-source web applications showed that (1) carved API tests achieve similar coverage as the UI tests that they are created from, but with significantly less (10x) execution time, (2) APICARV achieves high precision in inferring API specifications, and (3) APICARV can increase the coverage achieved by automated API test generators.

There are several directions in which our approach could be extended in future work, including development of techniques for improving the inferred specifications to take them closer to developer-written specifications, enhancing the specifications with information (e.g., example values) that can be leveraged by automated REST API test generators, and improving the recall of specification inference via novel crawling techniques aimed at discovering the server-side APIs of a web application.

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